

A MANAGEMENT SYSTEM FOR ELECTRIC VEHICLES TO OPTIMIZE THE ALLOCATION OF CHARGING PROCESSES ON MOTORWAYS

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ABSTRACT

In the coming years, the number of electric vehicles (EVs) is going to increase, while the charging network might not be adequately expanded at the required time. It is very likely that there will be feedback effects within the power grid in form of capacity bottlenecks. This might result in reduced charging power for a higher number of electric vehicles in order to counteract fluctuations. In this paper, the authors describe a management system for electric vehicles that optimizes the allocation of charging processes on motorways. The designed system aims to optimize travel and charging times while reducing waiting times for electric vehicles in intercity transport. By considering respective charging capacities, it may be able to reduce feedback effects with the energy system. The management system uses data from the charging stations, electric vehicles and their planned route. This allows the system to forward relevant information regarding expected energy demand to the power grid. Consequently, vehicles periodically communicate their position, battery level and their remaining way to destination to the management system, which returns charging advice for the optimal charging station. By using an optimization algorithm, the scarce resource of the charging stations is efficiently allocated to the vehicles. In order to examine its efficiency, a model of the management system with reduced features is transferred into a simulation. The simulation study follows an academic approach and takes different penetration rates of electric vehicles into account. A heuristic approach led to a solution with reasonable complexity, i.e. polynomial running time. In comparison, an analytical solution was outlined which describes the optimal case. This simulation study shows that the proposed system manages the waiting times efficiently by smartly assigning the vehicles to the corresponding charging stations.

Keywords: allocation, charging stations, electric vehicles, management system, motorway.

1 INTRODUCTION

The European Union seeks to achieve the goal of climate-friendly mobility. In order to reach climate neutrality in the transport sector and minimize the dependence of the transport industry on fossil fuels, a common strategy is being pursued throughout Europe [1]. To realize climate-friendly mobility, the European Commission has proposed a first EU climate law with the goal to make the EU climate-neutral by 2050 [2, 3]. The federal government of Germany has also defined a goal of halving greenhouse gases by 2023 and promoting electromobility [4]. Specifically, according to the federal government's goal, seven to ten million electric vehicles should be registered in Germany by 2030 [5]. This seems particularly reasonable as alternative fuels since replacements for combustion engines (e.g. e-fuels, power-to-x) will not be available in sufficient quantities by 2030 [6]. Furthermore, the study by Dörr et al. [6] states that batteries for electric vehicles are sufficiently developed for everyday mobility purposes. Yet, additional optimization is anticipated, resulting in longer ranges and thus more diverse usage. Based on these framework conditions, an increased growth in electric vehicles is to be expected in the next few years. Growth is being further influenced by the pressure to act on climate policy and the measures and incentives that have been created.

Compared to combustion engines, electric vehicles have different ranges and different refuelling or rather charging behaviour. Their motion energy is made accessible to the drivers via the underlying charging technology and the associated charging infrastructure. In order to

ensure the required electric energy supply to the electric vehicles, it is mandatory to balance the increasing number of electromobile consumers, the volatile feed-in of renewable energy sources and the availability of charging stations with a management of charging processes. According to [7], around 220.000 electric vehicles were registered in Germany in 2019, resulting in a 0.64% market share of battery electric vehicles (BEVs) and a 0.58% share of plug-in hybrid electric vehicles (PHEVs) of all passenger cars in Germany [8] (see Fig. 1). In 2019, there were 21,100 publicly accessible charging points. The aim of the German Federal Government is to extend the charging infrastructure to one million charging points by 2030. With regard to the charging of battery-operated vehicles, there are three essential approaches: charging with alternating current (AC charging), charging with direct current (DC charging, fast and high-performance charging) and non-wired inductive charging [9]. The latter approach will play a minor role until 2030; until it is adequately available. The study by Dörr et al. [6] shows a lack of uniform regulations on the part of the EU, as well as currently extremely high costs of technology. It can be assumed that the development of approaches and prototypes in the field of charging technologies will be widely dynamic and diverse.

Many scientific publications deal with the assessment of future charging demand and the need of an optimal distribution of charging stations in the road network. The analysis tool CURRENT (charging infrastructure for electric vehicles analysis tool, see [10, 11]) uses MiD data (traffic survey ‘**M**obilität in **D**eutschland’, mobility in Germany) as input, assumptions on charging behaviour as well as infrastructure data. Applying the tool as pivotal output, one obtains the demand for charging infrastructure, divided into different types of charging technologies. CURRENT has been applied in many different projects so far. In [10], for example, the authors analyse the demand for charging infrastructure in long-distance traffic, considering typical usage patterns, derived from the car usage model CUMILE (Car Usage Model Integrating Long-Distance Events) and the traffic model Validate. In order to determine cost-minimized energy mixes with renewable energies, the REMix (Sustainable Renewable Energy Mix for Europe) model [12] delivers suitable information. This model applies a linear optimization to a geographic information system (GIS)-based, temporally and spatially highly resolved inventory of the power generation potential of renewable energy.

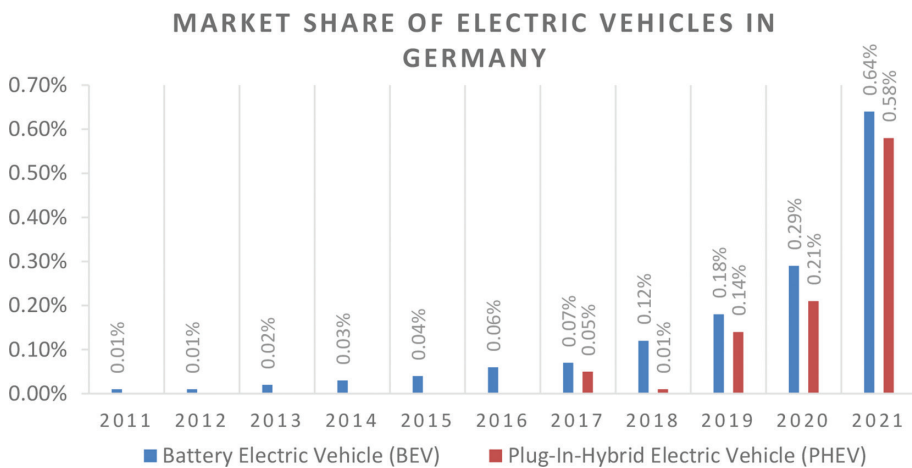


Figure 1: Market share of electric vehicles in Germany from 2011 to 2021 (Source: Statista 2021 [8]).

With the increasing number of electric vehicles and the volatile feed-in of 65% renewable energies (according to the coalition agreement for the formation of the German Federal Government in 2018), interactions with the power grid are to be expected. Therefore, the charging processes and the resulting additional load on the power grid must be managed in order to avoid critical grid situations and to maintain the grid stability [6].

Problem: It can be assumed that the operation of charging stations is based on economic principles. Hence, there will be a balance between the expected demand (with revenue opportunities) and the operating costs when choosing a location and a number of charging stations. The consequence is that there will be no oversupply of charging stations in a realistic scenario. Especially at unattractive locations, there will rather be a shortage of charging opportunities. Furthermore, extension of charging infrastructure is only reasonable from an economic point of view, if there is a sufficient increase of demand. This possibly leads to further shortages of available charging stations. With a higher number of electric vehicles, there will be feedback effects with the power grid due to short-term changes in the electricity demand. Feedback effects can primarily be regulated via the energy price. This seems to be a good instrument for short trips in the city. For long-distance trips, this instrument is only partially helpful, where many vehicles are forced to charge. In order to avoid critical network situations, the charging station will reduce the power ranges if necessary. Conversely, this leads to longer loading times, an increase to travel times and, in case of a high traffic scenario, to longer waiting times.

In order to solve this problem, a management system needs to optimally allocate the scarce resource ‘charging station’, to minimize charging gaps, to know about power bottlenecks of the energy supply system and to consider all relevant information of involved system components. In the literature, there are approaches that consider the dynamic allocation of electric vehicles and the reservation of charging stations: Cassandras and Geng [13] propose an optimal allocation and reservation system for electric vehicles at charging stations, which is distributed in an urban environment. The approach is similar to ‘smart parking’. It allocates and reserves an optimal spot at a charging station. The optimization is based on the user’s cost function in relation to the proximity to the location or destination and the charging costs. Users make reservations at charging stations on demand. At their request, they can also enter further ‘constraints’. Subsequently, the system computes suitable charging possibilities. For optimization purposes, the computation is repeated periodically.

The existing scientific approaches to managing charging processes of electric vehicles are optimizing from the point of view of a single user or a single fleet. In contrast, our approach centrally calculates the optimal assignment of charging processes, with a feedback loop to all electric vehicles. The approach is described in Section 2. Section 3 contains the simulation study with a discussion of the results. Finally, future investigations will be discussed in the outlook.

2 SOLUTION APPROACH AND CONCEPTUAL DESCRIPTION

While the charging of electric vehicles for short distances can often be arranged more flexibly by the user, this flexibility is missing in long-distance traffic, especially when the vehicle needs to be charged in order to reach its destination. As shown in the introduction, the obtained approaches pursue the optimization from the point of view of the individual driver or user. The approach dealt within this paper optimizes from an overall system perspective. There are two objectives. The first objective is the minimization of travel and charging times for electric vehicles in long-distance traffic through the optimal allocation and reservation of charging points. The second objective is to provide the forecasted electricity demand to the

electricity supplier. The feedback from the electricity supplier can be used afterwards to adjust the allocation of charging stations for the purpose of power grid stability.

2.1 Implementation concept

The following requirements apply to the management system.

Predictability of electricity demand: Changes in the demand for electricity should be predictable and communicated to the energy supplier/charging station operator. If there are bottlenecks in the power supply, this should be considered as early as possible in the allocation.

Reduction of waiting times at charging stations: It can be assumed that charging stations will remain a scarce resource. Especially for high traffic scenarios (weekend/holiday traffic), there will probably be bottlenecks and longer waiting times. Requirements include minimizing waiting times at the charging station.

Optimal use of capacity of the charging stations and spatial distribution: Within the moderate traffic scenario, local bottlenecks at charging stations can occur, while other charging stations have free capacities. Here, there is a requirement for an optimal distribution of the vehicles, considering the vehicle parameters and route planning. The minimization of the charging gaps represents a further point for optimizing.

Transparency from the user's point of view: Price and economic aspects are not considered in this paper. However, it can be assumed that there are requirements with regard to price transparency and liability of the assigned charging points.

Figure 2 shows the system concept of the proposed management system. It is a conceptual draft. In the following, the components of the management system are explained. The core of

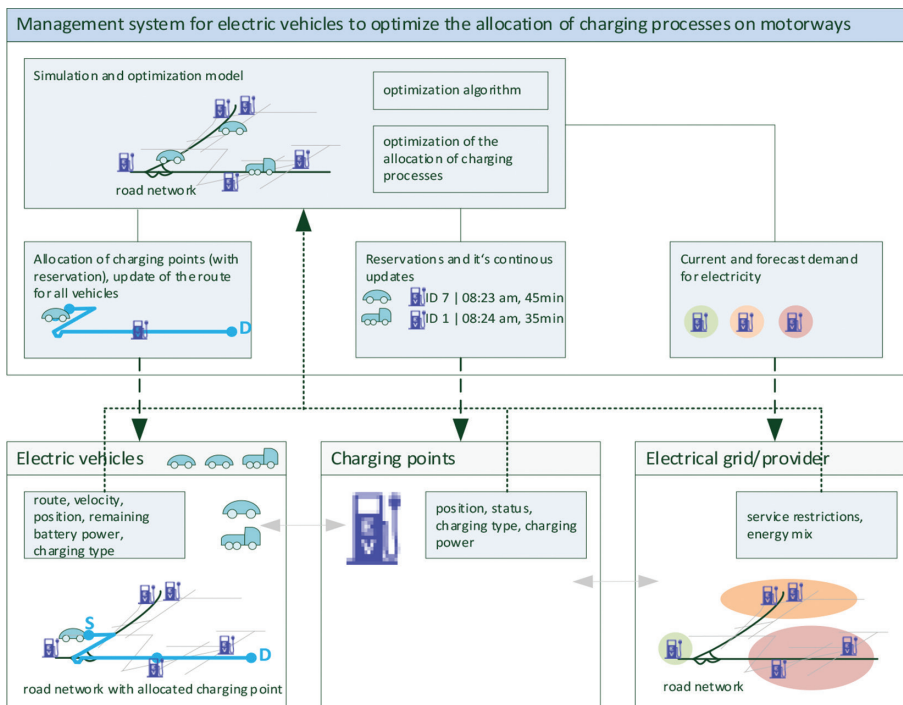


Figure 2: System concept and components.

the management system represents an optimization algorithm. For instance, it can be based on a real-time capable microscopic traffic flow simulation using real-time input data. As can be easily seen, finding the distribution with minimal total waiting time of n vehicles at k charging stations equals to the problem of finding all k -subsets of a set with n elements, i.e. an optimal solution has running time $O\left(\binom{n}{k}\right) = O(n!)$, which is too expensive. Therefore, finding an algorithm with acceptable running time is of great importance. The designed algorithm for this particular problem is explained in the next section and implemented in the simulation study.

For processing, the system continuously needs at least the following data. The system knows all electric vehicles in its operating area, the type of vehicles, their routes or route sections, their current position and travel speed, their remaining battery energy and thus the remaining kilometres, and the maximum charging speed of the vehicle, including the consideration of the battery temperature. With regard to the charging stations, the system has access to metadata such as the locations of all relevant charging stations, charging type, operating status and charging power. At the least, the information on the energy mix and service restrictions should be known from the power grid or electricity supplier.

The optimization algorithm continuously calculates the best possible allocation of the charging points. Here, it uses the data of the vehicle, the charging stations and the power grid in a next step. Assigned charging stations are communicated to the vehicle. The vehicle may receive a route update. Furthermore, the slot for charging at the charging station is reserved for the vehicle. The demand in the power grid can be predicted via the management system, as it knows the energy demand of all electric cars at the corresponding route. In addition to that, the system precisely predicts the energy demand as soon as a vehicle receives an allocation to a charging point. The traffic situation is a further variable of the system. It is possible to predict the traffic and following, optimize the allocation of the charging stations.

In the performed simulation study, some properties of the system described here were implemented and simulated.

3 ALGORITHM

The main idea behind the design of the algorithm for allocating an electric vehicle on a route on the motorway to a specific charging point was to keep the average waiting times of the vehicles at the charging stations as low as possible. From a system perspective, this can be made possible by balancing the distribution of vehicles to charging stations. At first, the running time of an optimal approach for the allocation is computed. To model the road network, a straight (highway) road in one direction is chosen, with starting point A and end point B , and k exits, each leading to a charging station. The exits follow the road at equal intervals of length d . In Fig. 3, the road network is illustrated.

In order to find the distribution with minimal waiting time, we need to consider every single permutation of the n vehicles at the k charging points and pick the one with the least waiting time in total. Using combinatorics [14], we derive $\binom{n}{k}$ possibilities. Consequently,

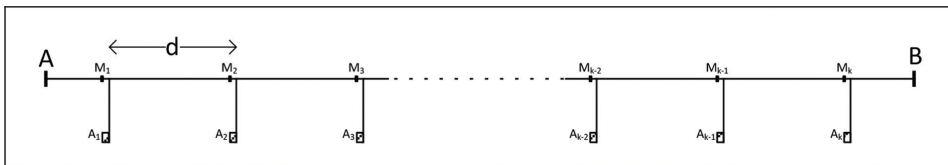


Figure 3: Simplified model of a one-way motorway with equidistant exits to charging stations A_1, A_2, \dots, A_k .

an algorithm that realizes an optimal distribution of vehicles to charging stations has a non-polynomial (NP) running time. Thus, a heuristic approach is tried.

We consider each vehicle which needs to charge on its way to the destination in regular distances, at so-called decision points. In Fig. 3, the decision points are marked with M_1, M_2, \dots, M_k . If an electric vehicle has insufficient charging power to reach its final destination and reaches a decision point M , the system compares the waiting time at the immediate following charging station with the current average waiting time of the next j charging stations on the route. Here, j is the number of the following charging stations that can still be reached with the current charge. If the waiting time at the nearest charging station is shorter than the current average waiting time at the following charging stations, the management system gives the vehicle an instruction to charge at the nearest charging station. Otherwise, the vehicle is instructed to continue driving. In this way, the perspective waiting time at a more distant charging station is estimated by the current average waiting time of the following charging stations. It is clear to the authors that this is only a certain approximation. As described earlier, the focus is on finding a feasible solution with acceptable computational complexity. The complexity of the described algorithm is $O(k^2 \cdot n) = O(n)$, i.e. the algorithm runs in polynomial time, which is exactly what we were looking for.

3.1 Algorithm in pseudocode

In what follows, the road network in Fig. 3 is considered.

Definitions:

1. For $i \in \{1, \dots, k\}$, decision point M_i is defined as a point lying at a specific, preferably short distance in front of the junction leading to A_i , so that at this point a vehicle is still able to take the exit to A_i .
2. $t_{wait,k}$ is current waiting time at charging station A_k .

Pseudocode:

Whenever a vehicle v crosses a decision point M_i and its battery level does not admit to being able to reach destination point B , the system runs method `get_charging_advice` for vehicle v .

Method `get_charging_advice` (vehicle v , decision point M_i) {

Al : = last possible charging station to reach B regarding battery level of v .

$$\overline{t_{wait}} = \frac{1}{|l - (i + 1)|} \sum_{k=i+1}^l t_{wait,k} \quad \text{*compute the intermediate waiting time } \overline{t_{wait}} \text{ regarding stations } A_{i+1}, \dots, A_l$$

$$\text{if } t_{wait,k} \leq \overline{t_{wait}} \{$$

send vehicle v a request to charge.

}

else {

go ahead on the motorway.

}

4 SIMULATION STUDY

In order to test the algorithm defined in the last section, a simulation study was conducted. The simulation framework used for the study was the microscopic traffic flow simulator SUMO (Simulation of Urban Mobility) [15]. An important reason to use SUMO is the ability to interact with simulation objects during runtime through TraCI (Traffic Control Interface) [16]. Not only is it possible to obtain specific parameters of objects (e.g. positions and speeds), but one can also manipulate many parameters in order to model traffic management measures (e.g. set routes, add stops and set speeds). Furthermore, SUMO provides an energy consumption model that also includes charging processes of electric vehicles [17]. An overview about the model of electric vehicles and their traffic behaviour can be found in [18]. The energy model merely has to be parameterized to match the model assumptions; see [21].

Another reason to choose SUMO is its many options when it comes to enhance the simulation in a second step. SUMO offers Hardware-In-the-Loop simulation [19], covers demand-responsive transport (DRT) simulations and is able to model emissions [20]. In addition, it is also possible to couple SUMO with another simulator [21]. The values of the parameters used in our simulation study are listed in Table 1. Hence, there is a wide range of opportunities for a later extension of the current simulation.

The simulation study includes two scenarios:

- **No optimization:** Vehicles may charge as they desire, and there is no regulatory instance that manages charging processes.
- **Management system:** Central regulatory instance manages charging processes and distributes them according to the previously defined optimization algorithm.

To account for modelling errors, multiple simulation runs with different random seeds are executed. Afterwards, the simulation results are averaged over all random seeds. Therewith, a Monte Carlo experiment is performed. The more seeds are run, the better the approximation of the expected value of the average waiting time at a charging station. Different optimization levels for different volumes are expected. Therefore, an input parameter is implemented to depict different traffic volumes. Traffic volumes in the simulation correspond to penetration rates of electric vehicles in real mixed traffic. Considering the road network in Fig. 3, we set

1. Distance $\overline{AB} : = 400,000 \text{ m} = 400 \text{ km}$.
2. Distance between charging station $|A_i A_{i+1}| = 10,000 \text{ m} = 10 \text{ km}$.
3. Decision point M_i is at 150 m distance in front of the junction leading to A_i .
4. Every charging station A_i is equipped with exactly one charger.

All vehicles start at point A with a random battery capacity which is not lower than 40% of the total capacity. The route leads straight to destination B. In a first step, we start with $1 \leq n \leq 100$ vehicles per hour of traffic volume. As a second step, we consider $200 \leq n \leq 2000$ vehicles per hour. To relate these numbers with actual rates of electric vehicles, we use Fig. 1, which shows the market share of electric vehicles in Germany over the past 10 years. Thus, the actual rate of 0.64% is represented by a given $n = 25$. A rate of 25% is represented by $n = 1000$. In the simulation, we load vehicles into the road network for one hour and record each travel time and waiting time at a charging station. In the case of no optimization, vehicles choose to charge if and only if their battery level does not allow them to reach a further charging station

Table 1: Applied parameters to the SUMO energy model.

Energy model in SUMO with suitable parameterization	
Parameter	Value
Maximum speed	41.67 m/s
Maximum battery capacity	70,000 W
Maximum power	100,000 W
Vehicle mass	1615 kg
Front surface area	3 m ²
Air drag coefficient	0.6
Internal moment of inertia	0.01
Radial drag coefficient	0.5
Roll drag coefficient	0.01
Constant power intake	0 W
Propulsion efficiency	0.9
Recuperation efficiency	0.9
Stopping threshold	0.1

than the subsequent one. During simulation runs with management system, the vehicles are allocated to a charging station by the algorithm in Section 3.1. Their respective charging time results from the actual battery level and the energy consumption model in SUMO.

5 RESULTS

After executing 230 seeds for different density of electric vehicles, the data collection shown in Table 2 is obtained. Having a closer look, it is seen that for a traffic volume of n electric vehicles, with $n \leq 1000$, remarkable optimization results are gained:

1. For $n \leq 300$, the average waiting time at a charging station was reduced by more than 50% when using the management system.
2. For $n \leq 1000$, the average waiting time at a charging station was reduced by more than 20% when using the management system.
3. For $n > 1000$, there is little to no optimization when using the management system, at least when there is only one charger per charging station.

For small numbers of electric vehicles per hour, results were gained very quickly, as the waiting time is rather low, referring to Table 2. At the beginning of our simulation runs, all 20 seeds were gained as planned. However, the higher n is, the higher waiting times are, which led to very long simulation runs. For example, for $n = 1000$, the waiting time is about 18 hours, leading to very high running times in the simulation. As a consequence, for higher n , there are data sets with only one seed. It is clear to the authors that the results of these runs are much less representative. Yet, compared to each other, the data sets are consistent.

In Figs. 4 and 5, the data from Table 2 were plotted into a graph to visualize the effectiveness of the management system for smaller n , as well as to illustrate the immense waiting times for higher n .

Table 2: Simulation results.

Electric vehicles per hour	Seeds run through	Waiting time per electric vehicles in minutes	
		Without management system	With management system
1	20	0	0
5	20	3	1
10	20	7	3
20	20	16	6
30	20	29	15
40	20	43	19
50	20	50	22
75	20	82	38
100	13	107	43
200	19	249	113
300	10	389	201
400	6	497	312
500	16	637	431
1000	3	1338	1083
1500	1	1973	1952
2000	1	2714	2678
2500	1	3207	2994

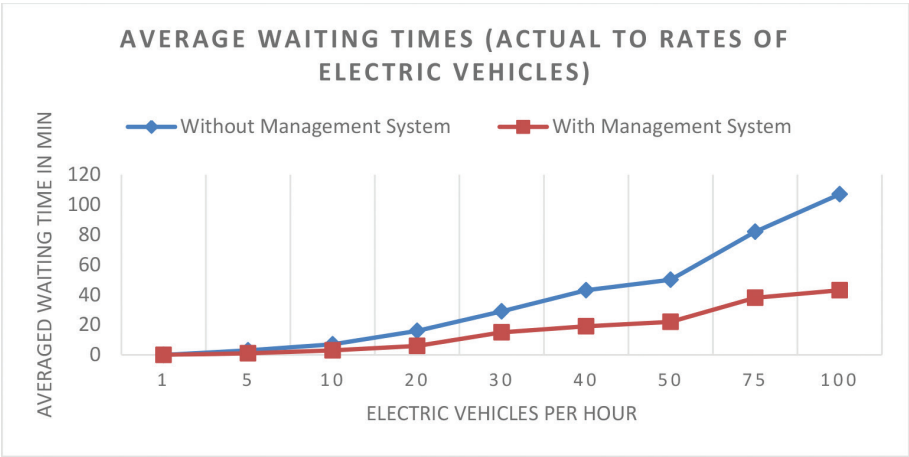


Figure 4: Results for $n = 1, \dots, 100$.

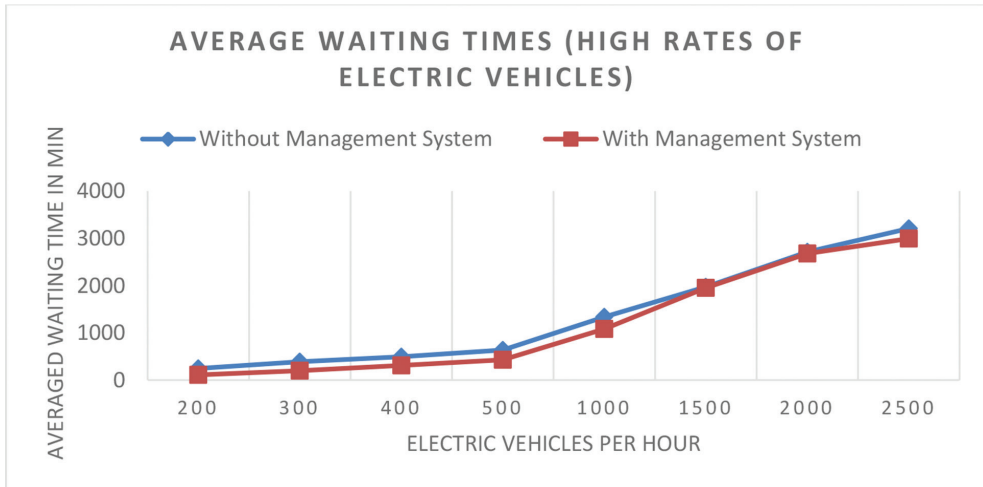


Figure 5: Results for $n = 200, \dots, 2500$ (note the different time scale on the y-axis).

6 OUTLOOK

In future investigations, we plan to find suitable simulation settings to also obtain useful results for higher densities of electric vehicles. As a first step, simulations will be run with higher numbers of chargers per charging station, aiming to find a balance between traffic volume of electric vehicles and charging stations, so that waiting times are equivalent to those of smaller number of electric vehicles.

Furthermore, we will try to calculate optimal waiting times for each run by implementing an analytical solution at the beginning of each simulation. Consequently, a benchmark for the optimization level of the designed algorithm would be obtained and the deviation of the heuristic solution from the optimum could be measured.

REFERENCES

- [1] European Commission. Communication from the Commission of the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: Sustainable and Smart Mobility Strategy – putting European transport on track for the future [COM/2020/789 final]. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0789>; Accessed on: 09.03.2021
- [2] European Commission. Amended proposal for a Regulation of the European Parliament and of the Council on establishing the framework for achieving climate neutrality and amending Regulation (EU) 2018/1999 (European Climate Law) [COM/2020/563 final]. https://ec.europa.eu/clima/sites/default/files/eu-climate-action/docs/prop_reg_ecl_en.pdf; Stand: 03.03.2021
- [3] Verband der Automobilindustrie. Europa braucht Balance zwischen Klimaschutz und Wettbewerbsfähigkeit. <https://www.vda.de/de/presse/Pressemeldungen/20200304-europa-braucht-balance-zwischen-klimaschutz-und-wettbewerbsfaehigkeit.html>; Accessed on: 03.03.2021
- [4] Bundesregierung. Ziele der Bundesregierung: Bis 2030 die Treibhausgase halbieren. <https://www.bundesregierung.de/breg-de/themen/klimaschutz/klimaziele-und-sektoren-1669268>; Accessed on: 03.03.2021

- [5] Bundesregierung. Mehr E-Mobilität (03.03.2021). <https://www.bundesregierung.de/breg-de/themen/klimaschutz/verkehr-1672896>; Accessed on: 03.03.2021
- [6] Dörr, N., Dörmann, L., Klebsch, W. & Oleniczak, A., Logistik, Energie und Mobilität 2030: Metastudie im BMWi Technologieprogramm IKT für Elektromobilität, Berlin. <https://www.vde.com/resource/blob/2013758/3e6f90ce5a2bf8baee20f0056bc4f3b9/studie-logistik-mobilitaet-und-energie-2030-data.pdf>; Stand: 21.03.2021
- [7] Bundesregierung. Masterplan Ladeinfrastruktur: Mehr Ladestationen für Elektroautos. <https://www.bundesregierung.de/breg-de/themen/klimaschutz/ladeinfrastruktur-1692644>; Accessed on: 09.03.2021
- [8] Statista. Elektromobilität - Anzahl der reinen Elektro-Pkw und Plug-in Hybride in Deutschland bis 2022 | Statista. <https://de.statista.com/statistik/daten/studie/1076854/umfrage/bestand-an-bev-und-phev-in-deutschland/>; Accessed on: 19.04.2021
- [9] DKE Deutsche Kommission Elektrotechnik Elektronik Informationstechnik in DIN und VDE. Der Technische Leitfaden Ladeinfrastruktur Elektromobilität. <https://www.dke.de/resource/blob/988408/ca81c83d2549a5e89a4f63bbd29e80c6/technischer-leitfaden-ladeinfrastruktur-elektromobilitaet---version-3-1-data.pdf>; Accessed on: 03.03.2021
- [10] Anderson, J.E., Bergfeld, M., Chlond, B., Friedrich, H.E., Hoffmann, N., Lenz, B., Kleiner, F., Klötzke, M., Kuhnimhof, T., Schmid, S., Soyly, T., Steck, F. & Wei, C., LADEN2020 Schlussbericht: Konzept zum Aufbau einer bedarfsgerechten Ladeinfrastruktur in Deutschland von heute bis 2020. <https://elib.dlr.de/111054/> Accessed on: 19.04.2021
- [11] Anderson, J.E., Steck, F. & Kuhnimhof, T., Can renewable energy sources meet electric vehicle charging demand today and in the future? A microscopic time-specific travel demand analysis for Germany, Transportation Research Board 97th Annual Meeting, 2018.
- [12] Luca de Tena, D., Large scale renewable power integration with electric vehicles [Stuttgart, Universität Stuttgart, Diss., 2014]. Stuttgart: Universitätsbibliothek der Universität Stuttgart, 2014.
- [13] Cassandras, C.G. & Geng, Y., Optimal dynamic allocation and space reservation for electric vehicles at charging stations. *IFAC Proceedings Volumes*, **47(3)**, pp. 4056–4061, 2014. <https://doi.org/10.3182/20140824-6-ZA-1003.01041>
- [14] Cameron, P.J., *Combinatorics: Topics, Techniques, Algorithms*, 1st ed., Cambridge: University Press: Cambridge, pp. 22–24, 1994.
- [15] Eclipse SUMO - Simulation of Urban MObility. Eclipse SUMO - Simulation of Urban MObility. <https://www.eclipse.org/sumo/>; Accessed on: 19.04.2021
- [16] TraCI - SUMO Documentation. <https://sumo.dlr.de/docs/TraCI.html>; Accessed on: 19.04.2021
- [17] Kurczveil, T., López, P.A. & Schnieder, E., Implementation of an energy model and a charging infrastructure in SUMO. *Simulation of Urban Mobility*, eds. M. Behrisch, D. Krajzewicz & M. Weber, Lecture Notes in Computer Science, Springer, pp. 33–43, 2014.
- [18] Ruppe, S. & Wesemeyer, D., Simulation einer elektrifizierten Busflotte mit SUMO: MENDEL: Minimale Belastung elektrischer Netze durch Ladevorgänge von Elektrobussen, *ITS Word Congress*, 2017. <https://core.ac.uk/reader/220158797> Accessed on: 19.04.2021
- [19] Markowski, R., Aufbau einer mikroskopischen Verkehrsflusssimulation in SUMO mit einer echtzeitfähigen Datenanbindung an ein LSA-Steuergerät [Studienarbeit]. Technische Universität Dresden, 2016.

- [20] Krajzewicz, D., Behrisch, M., Wagner, P., et al., Second generation of pollutant emission models for SUMO. *Modeling Mobility with Open Data: 2nd SUMO Conference*, eds. M. Behrisch & M. Weber, Berlin, Germany, May 15-16, 2014, Springer International Publishing: Cham, pp. 203–221, 2015.
- [21] Bottazzi, M., Touko Tcheumadjeu, L.C., Trumpold, J., Erdmann, J. & Oertel, R., LiSuM: Design and Development of a Middleware to couple Virtual LISA+ TLS Controller and SUMO Simulation, SUMO User Conference 2017, Berlin, May 8–10th, 2017.